

METHOD AND APPARATUS FOR  
SEGMENTING SMALL STRUCTURES  
IN IMAGES

Cross-Reference to Related Applications

The present invention is related to the subject matter of provisional patent application Serial No. 60/084,125 filed on May 4, 1998, the entire disclosure of which is incorporated herein by reference.

5 Field of the Invention

The present invention relates to data processing of intensity data arranged in a multidimensional array. More particularly, the invention relates to a method, an apparatus, and computer program products for rapidly segmenting multidimensional intensity data by which points in one or more small structures  
10 contained in the data are labeled.

Background of the Invention

Digital imagery and other multidimensional digital arrays of intensity are routinely collected using digital sensors and arrays of charge coupled devices (CCDs). The resulting data arrays are analyzed to determine patterns and detect  
15 features in the data. For example, color images of a battle scene are analyzed to detect targets, and radiographs and sonograms of human and animal bodies are examined to detect tumors and other indications of injury or disease. As the number and complexity of these digital data arrays to be analyzed increase or the time required to perform the analyses decreases, automated and machine assisted  
20 analysis becomes more critical. Some statistically based automated procedures for detecting features in a multidimensional array are adequate when the feature encompasses many points in the array, i.e. when the feature is large, but fail to

perform well as the feature to be detected becomes small. Some procedures perform well when tuned to a particular problem through experimental adjustment of many parameters, but such tuning may place an undue burden on time limited or experience limited personnel. Typical problems encountered with such automated analysis of small structures in multidimensional arrays are illustrated for the case of automatic detection of microcalcification candidates in mammograms.

Breast cancer has the highest incidence among all cancer types in American women, causing 1 woman in 8 to develop the disease in her lifetime. Every year, about 182,000 new cases are diagnosed with breast cancer and about 46,000 women die of this disease. The 5-year survival for women with breast cancer improves significantly with early diagnosis and treatment. To enable early detection, the American Cancer Society (ACS) recommends a baseline mammogram for all women by the age of 40, a mammogram approximately every other year between the ages of 40 and 50, and a mammogram every year after the age of 50. It is possible that the volume of mammography will become one of the highest among clinical X-ray procedures since more than 30 million women in the US are above the age of 50 and 41% are known to follow the ACS guidelines.

Besides the volume problem, an additional difficulty of early detection of breast cancer in mammograms is the subtlety of the early signal. A microcalcification cluster, an early sign of breast cancer that may warrant biopsy, is commonly defined as three or more microcalcifications present in 1 cm<sup>2</sup> on a mammogram. These clusters are often difficult to detect due to their small size and their similarity to other tissue structures. The width of an individual microcalcification is less than 2 mm. The etiology of microcalcifications includes lobular, ductal or epithelial hyperplasia, secretion of calcium salts by epithelial cells, adenosis, as well as calcification of necrotic debris due to carcinoma. Up to 50% of breast cancer cases exhibit microcalcification clusters, and 20-35% of clusters in the absence of a mass are related to malignant growth. In many cases a cluster is the first and only sign that allows timely intervention.

The increasing pressure to interpret large numbers of mammograms and the subtlety of many early signs increase the likelihood of missing breast cancer. A reliable automated system that indicates suspicious structures in mammograms can allow the radiologist to focus rapidly on the relevant parts of the mammogram and it can increase the effectiveness and efficiency of radiology clinics. In the detection of breast cancer, false negatives may cause a delay in the diagnosis and treatment of the disease while false positives cause unwarranted biopsy examinations. Therefore, both sensitivity and specificity need to be maximized, with a relatively higher priority on sensitivity, which has a more vital role.

10        A common approach used for detecting microcalcifications in mammograms starts by segmenting candidate structures and subsequently applying feature extraction and pattern recognition to distinguish microcalcifications from background tissue among the candidates. In this process, segmentation plays an essential role since the quantitative features that represent each candidate structure, such as size, contrast, and sharpness, depend on the region indicated by segmentation. Furthermore, to process all possible candidate structures, a considerably large number of background structures need to be segmented, making fast segmentation desirable.

20        Several techniques for segmentation have been applied to microcalcifications. One segmentation technique is based on local thresholding for individual pixels using the mean pixel value and root mean square (rms) noise fluctuation in a selected region around the thresholded pixel. The threshold for a pixel is set as the mean value plus the rms noise value multiplied by a selected coefficient. A structure is segmented by connecting pixels that exceed the threshold. Both parameters that have to be selected, size of region and threshold coefficient, are critical to this method. If a microcalcification is close to another microcalcification or bright structure, the window used to compute the rms noise value around the first microcalcification will include the other bright structures, and the noise rms may be overestimated, thus setting the threshold too high. On

the other hand, if the selected region is too small, it will not contain sufficient background pixels when placed on large microcalcifications.

Such a window size needs to be selected in a second segmentation algorithm as well, where local thresholding is used by setting a threshold for small square sub images. The threshold is based on an expected bimodal intensity distribution in a window of selected size that contains the sub-image to be segmented. If the distribution is not bimodal, then the threshold is set by using 5 different positions of the window each containing the sub-image to be segmented. The existence of a bimodal distribution in at least one window is essential for this algorithm.

Other segmentation methods start with seed pixels and grow a region by adding pixels. They also require selection of a window size and threshold parameters. The localized implementation of region growing depends on the selected window size and the threshold for absolute difference in gray level between the seed pixel and a pixel to be added to the region.

One segmentation algorithm uses several steps that include high-pass filtering, difference of Gaussian filtering, four computations of the standard deviation of the image, a smoothing, an opening, as well as an iterative thickening process with two erosions, two intersections and a union operation in each iteration. More than ten parameters have to be selected, including widths of Gaussian distributions, threshold coefficients, and diameters of morphological filtering elements.

A segmentation algorithm that operates without parametric distribution models, local statistics windows, or manually adjustable thresholds is desirable.

A segmentation method that is fast is also important. Up to 400 films per day are routinely screened in busy radiology clinics. The automated analysis does not have to be applied on-line; however, it may be difficult to process large numbers of mammograms overnight if algorithms are not fast enough. Because the segmentation algorithm has to segment all candidate structures that may

potentially be microcalcifications, its speed is especially relevant. Each film may have several thousand candidate structures that must be segmented.

The multi-tolerance segmentation algorithm of Shen et al. (L. Shen, et al. "Detection and Classifications of Mammographic Calcifications," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 7, pp. 1403-1416, 1993), does not use statistical models for local statistics, and its threshold is set automatically. This multi-tolerance, region growing approach uses a growth tolerance parameter that changes in a small range with a step size that depends on the seed pixel. The structure of interest is segmented multiple times with varying tolerance parameters, and in each segmentation, a set of three features is computed. The normalized vector differences in the feature set between successive segmentations are calculated and the segmentation with minimal difference is selected as the final one.

The active contours model of Kass et al. (Kass, M. et al. "Snakes: Active Contour Models," *International Journal on Computer Vision*, pp. 321-331, 1988), also provides segmentation without parametric statistical data models or windows for local statistics, but does rely on several user selected parameters that place some burden on the user. It has been used successfully to determine the boundaries of tissue structures in data such as ultrasound and MRI images of the heart, and MRI images of the brain, but it has not been applied to the segmentation of microcalcifications. The active contours model starts with an initial contour placed near the expected boundary and moves the contour iteratively toward the boundary by minimizing an energy function. The contour is modeled as a physical flexible object with elasticity and rigidity properties. Its dynamics, dictated by the balance between these internal properties and external forces that depend on the image data, satisfy the Euler equations and minimize the corresponding energy function. An active contour that is initiated as a closed curve remains so during iterations and its smoothness can be adjusted by the choice of parameters.

What is needed is a segmentation method and apparatus without statistical models, local statistics, or thresholds to be selected manually, and with significantly lower computational complexity compared to the multi-tolerance and active contours methods, for enhanced speed.

- 5           In particular, what is needed is a method and apparatus to segment pixels in an image, such as a mammogram, containing a plurality of extra dark or extra bright objects just a few pixels in extent, that gives edges similar to those selected by an expert, but does so with fewer computations and with fewer manually adjustable parameters than conventional segmentation methods and equipment.

## 10   Summary of the Invention

Therefore it is an object of the present invention to provide segmentation for small features in multidimensional data which defines small feature edges that correspond closely to those selected by an analyst but does so with less complexity than the above known methods.

- 15           It is another object of the present invention to provide a data processing apparatus that more rapidly provides small feature edges that correspond closely to those selected by an analyst.

- It is another object of the present invention to provide computer program products that more rapidly provide small feature edges that correspond closely to those selected by an analyst.
- 20

          It is another object of the invention to identify microcalcifications in a mammogram.

- These and other objects and advantages of the present invention are provided by a method for segmenting a small feature in a multidimensional digital array of intensity values in a data processor. Each small feature includes a local intensity extreme, such as an intensity maximum. An edge metric is computed along each ray of a plurality of multidimensional rays originating at the local intensity extreme. A multidimensional edge point is identified corresponding to a
- 25

maximum edge metric on each ray. Every point on each ray from the local extreme to the ray edge point is labeled as part of the small feature. The labeling is then spread to an unlabeled point following a hill climbing procedure requiring that the unlabeled point be adjacent to a labeled point, have a similar or more  
5 extreme intensity than the labeled point, and be closer than the labeled point to the local extreme.

In another embodiment, the multidimensional array is a digital image, and each point is a pixel. In another embodiment, the digital image is a digitized mammogram and the small feature is a microcalcification candidate. In the latter  
10 embodiment, microcalcification candidates are satisfactory segmented in fewer operations than with conventional segmentation methods.

In another aspect of the invention, a data processing apparatus segments a small feature in a multidimensional digital array of intensity values. The apparatus includes an input for inputting a plurality of intensity values arranged  
15 along regular increments in each of a plurality of dimensions and a memory medium for storing the plurality of intensity values as a multidimensional digital array. The apparatus includes a processor configured to detect a local intensity extreme in the multidimensional digital array, to identify points along a plurality of rays originating at the local intensity extreme, and to identify one ray edge  
20 point on each ray. The ray edge point is associated with a maximum edge metric along the ray. The processor is also configured to label the points in the array that are part of the small features. Each point on each ray from the local intensity extreme to the edge point is labeled, as is an unlabeled point adjacent to a labeled point if the unlabeled point has a more extreme intensity than the labeled point  
25 and the unlabeled point is closer than the labeled point to the local extreme. Labeling continues until no more unlabeled points can be labeled. The apparatus also includes an output for providing the labeled points for subsequent processing.

In another aspect of the invention, a computer program product is provided for segmenting a small feature in a multidimensional array of intensities using a  
30 computer. The computer program product includes computer controlling

instructions for configuring a computer to compute an edge metric along each ray of a plurality of multidimensional rays originating at a local intensity extreme. The instructions also identify a ray edge multidimensional point corresponding to a maximum edge metric on each ray. The program also labels every point on each  
5 ray from the local extreme to the ray edge point, and then labels an unlabeled point if the unlabeled point is adjacent to a labeled point and the unlabeled point has a more extreme intensity than the labeled point, and the unlabeled point is closer than the labeled point to the local extreme. In one embodiment, the instructions are stored in a computer readable memory device. In another  
10 embodiment, the instructions are transmitted as electronic signals on a communications line.

The foregoing and other features, aspects and advantages of the present invention will become more apparent from the following detailed description of the present invention when taken in conjunction with the accompanying drawings.

#### 15 Brief Description of the Drawings

The preferred and example embodiments of the present invention are described with reference to the Drawings in which:

Figure 1A is a perspective view of the external features of a computer apparatus suitable for one embodiment of the present invention.

20 Figure 1B is a block diagram of a computer apparatus that can be configured according to one embodiment of the present invention.

Figure 1C is a perspective view of a sample memory medium for storing instructions to configure a computer according to another embodiment of the present invention.

25 Figure 1D is a block diagram of a network that can transmit electronic signals that configure a computer according to still another embodiment of the present invention.



Figure 2A is a flow diagram for a method according to yet another embodiment of the present invention.

Figure 2B is a flow diagram following step 270 of Figure 2A according to a further embodiment of the present invention.

5        Figure 2C is a flow diagram for details of step 260 of Figure 2A according to still another embodiment of the present invention.

Figure 2D is a flow diagram for an alternative detail for step 260 of Figure 2A according to yet another embodiment of the present invention.

10       Figure 3 is a schematic diagram of a local maximum, rays and edges that results from steps 210 through 250 of Figure 2.

Figure 4 is a schematic diagram of a local maximum, a labeled pixel, adjacent pixels, and a reference line according to one criteria for one embodiment of step 260 of Figure 2.

15       Figure 5 is a schematic diagram of a local maximum, a labeled pixel, and an adjacent pixel according to a criteria for another embodiment of step 260 of Figure 2.

Figures 6A-6D are gray scale photographs showing an actual intensity maximum as originally provided and then superposed with labeled pixels after three stages of the method of Figure 2 according to the present invention.

20       Figures 7A-7D are gray scale photographs showing three actual intensity maxima as originally provided and then superposed with labeled edge pixels after segmentation based on two conventional methods and the preferred embodiment of the present invention.

#### Detailed Description of the Preferred Embodiment

25       The principles of the present invention will be described next, detailed in terms of preferred and example embodiments with reference to the accompanying drawings. Whenever possible, the same reference numbers will be used throughout the drawings to refer to the same or like parts.

The explanations of the detailed embodiments are by way of example only and are not meant to limit the scope of the invention. The invention applies to identifying small structures in any multidimensional array of regularly spaced intensity values. Here intensity is used in a generic sense representative of measured data values in general, and is not confined to density of optical energy. Examples of such multidimensional arrays include gray-scale digital images in which intensity values are regularly spaced in two dimensions, often called rows and columns or y and x, such as the mammogram described in the preferred embodiment. In this kind of arrangement, each digital image element is a picture element called a pixel. Elevation maps are two dimensional arrays of height data, where height is the "intensity." Other examples of multidimensional arrays include color images which can be represented as three-dimensional arrays of intensity where the third dimension is color. Typically, the array would have intensity at only three points in the color dimension, for example, a red intensity, a blue intensity and a green intensity. Gray-scale video clips can also be considered three-dimensional arrays, where each video image frame is two-dimensional and the third dimension is time. By the same token, color video clips can be considered four-dimensional where the four dimensions are row, column, color and time. Other examples include medical imagery where two-dimensional cross sections of a human body are assembled at several positions from head to toe. In this case the third dimension is height through the subject. By extension, such three-dimensional looks can be repeated at uniform intervals of time, making time the fourth dimension. Thus the descriptions that follow apply not only to gray scale images of the preferred embodiment, but to multidimensional arrays of digital data.

A multidimensional point in a multidimensional digital array is located by the index of the point in each of the dimensions. Letting D represent the number of dimensions, the location of a multidimensional point P in a multidimensional array can be specified uniquely by a set containing D indexes as coordinates,  $\{I_1, I_2, I_3, \dots, I_D\}$ . Where there are only two dimensions, it is common to refer to  $I_1$  as

the x coordinate and to refer to  $I_2$  as the y coordinate. There is an implied limit to the number of allowed positions in each dimension of a finite array. Letting  $L_i$  represent the maximum number of locations in the i-th dimension of the digital data array, each index can vary from one to  $L_i$ , inclusive. That is:

$$5 \quad 1 \leq I_i \leq L_i. \quad (1)$$

The distance,  $d$ , between any two multidimensional points,  $P_a$  and  $P_b$ , with different indices  $\{a_1, a_2, a_3, \dots, a_D\}$  and  $\{b_1, b_2, b_3, \dots, b_D\}$ , can be defined as the square root of the sum of the squares of the differences in their indices. That is,

$$10 \quad \begin{aligned} d(P_a, P_b) &= d(P(a_1, a_2, \dots, a_D), P(b_1, b_2, \dots, b_D)) \\ &= \sqrt{[(b_1 - a_1)^2 + (b_2 - a_2)^2 + \dots + (b_D - a_D)^2]} \end{aligned} \quad (2)$$

The intensity,  $f$ , varies with position in the multidimensional array and may be represented by the symbol  $f(P)$ . The intensity  $f$  at each multidimensional point can be a single value, also called a scalar quantity. Alternatively, the intensity can be a vector of several values, e.g.,  $f(P) = \{f_1(P), f_2(P), f_3(P)\}$ . For example, the three-color image can be treated as a three-dimensional array or can be treated as a two dimensional image with a three element vector intensity. In this terminology, the vector elements of the intensity are not used in the calculation of distance using Equation 2. Instead, the magnitude of intensity at point  $P$  could be any vector magnitude convention such as the square root of the sum of the squares of the vector components or the sum of the absolute values of the vector components. Similarly, the difference in intensity between two points  $P_a$  and  $P_b$  would be given by the magnitude of the difference in the components using any conventional method.

25 Thus, though the preferred embodiment is described in which the digital data array is an image having two dimensional pixels, each pixel having a scalar image intensity, the method can readily be extended to multiple dimensions using the above relationships. In the following, each pixel  $P$  has a first coordinate represented by  $x$  and a second coordinate represented by  $y$  and an intensity

represented by  $f(P)$  or  $f(x,y)$ . Separate pixels are designated by separate subscripts.

Though the invention applies to any imagery, the preferred embodiments segment two-dimensional images with a gray-scale intensity representative of a mammogram. Other two dimensional imagery which the present invention can  
5 segment include imagery of military scenes in which the intensity is responsive to the presence of targets of a firing system, such as vehicles to be fired upon by a missile.

The invention is related to finding small objects in a multidimensional  
10 array. In this context small means objects affecting the intensity in several points in one dimension of the array but not many thousands of points in each dimension. Other, statistical and textural segmentation procedures, for example, are expected to be more useful as the number of points in a feature increases. It is characteristic of microcalcifications in mammograms and distant targets in  
15 military scenarios that only several pixels are contained in the object to be segmented. It is also anticipated that many other features to be detected in radiographs and sonograms of biological bodies also involve only several pixels. The present invention is expected to perform especially well for these applications.

20 The methods and procedures discussed herein are intended to be performed by data processing systems or other machines. Though described in terms that can be interpreted to be performed by a human operator, such performance is neither required nor likely to be desirable. Multiple tedious computations with high accuracy are required that are unsuitable for practical  
25 implementation by human beings. Also, the invention can be implemented in computer or other hardware, the structure of which is evident from the following descriptions.

Also herein, the procedures will be described as the manipulation of values, symbols, characters, numbers, or other such terms. Though such terms  
30 can refer to mental abstractions, herein they are used as convenient expressions

for physical signals such as controllable chemical, biological, and electronic and other physical states that can be used to represent the values, symbols, characters, numbers, or other such terms.

Figure 1A illustrates a computer of a type suitable for carrying out the invention. Viewed externally in Figure 1A, a computer system has a central processing unit 100 having disk drives 110A and 110B. Disk drive indications 110A and 110B are merely symbolic of a number of disk drives that might be accommodated by the computer system. Typically these would include a floppy disk drive such as 110A, a hard disk drive (not shown externally) and a CD-ROM drive indicated by slot 110B. The number and type of drives vary, typically, with different computer configurations. The computer has a display 120 upon which information is displayed. A keyboard 130 and mouse 140 are typically also available as input devices.

Figure 1B illustrates a block diagram of the internal hardware of the computer of Figure 1A. A bus 150 serves as the main information highway interconnecting the other components to the computer. CPU 155 is the central processing unit of the system, performing calculations and logic operations required to execute programs. Read-Only-Memory 160 and Random-Access-Memory 165 constitute the main memory of the computer. Disk controller 170 interfaces one or more disk drives to the system bus 150. These disk drives may be floppy disks drives, such as 173, internal or external hard drives, such as 172, or CD-ROM or DVD (digital video disk) drives such as 171. A display interface 125 interfaces a display 120 and permits information from the bus to be viewed on the display 120. Communications with external devices can occur over communications port 175.

Figure 1C illustrates an exemplary memory medium which can be used with drives such as 173 in Figure 1B or 110A in Figure 1A. Typically, memory media such as a floppy disk, or CD-ROM, or DVD, will contain the program information for controlling the computer to enable the computer to perform its functions in accordance with the invention.

Figure 1D is a block diagram of a network architecture suitable for carrying data and programs over communication lines in accordance with some aspects of the inventions. A network 190 serves to connect a user computer or client computer 110 with one or more servers such as server 195 for the download  
5 of program and data information. A second user on a second client computer 100' can also connect to the network via a network service provider, such as ISP 180.

In general, small objects in images may have an intensity level that is either lower or higher than a surrounding background. An intensity maximum with levels higher than the background is called a local maximum, and an  
10 intensity minimum with intensity levels below the background is called a local minimum. Both maximum and minimum are encompassed by the term intensity extreme. Thus, in general, the target objects in an image or multi-dimensional array encompass intensity extremes. Both are capable of being segmented according to the present invention. For the sake of serving as an example, the  
15 following description generally considers the preferred embodiment in which microcalcifications are evident as local maxima in intensity, and the method will be called a hill climbing method; however, segmenting a local minimum is also anticipated using the hill climbing method. In the following discussion, when a first point has an intensity equaling the intensity of the local extreme or between  
20 the intensity of the local extreme and the intensity of a second point, the first point is said to have a more extreme intensity than the second point.

Figure 2A shows the method according to one embodiment of the present invention. A local brightness maximum, characteristic of a microcalcification, is identified at pixel  $P_0$  in an image at step 210. Next, a plurality of rays is defined  
25 that emanate from that local maximum pixel  $P_0$  as illustrated in step 220. Figure 3 illustrates five sample rays 320 emanating from a local maximum 310. Referring again to Figure 2A, an edge metric is computed for each pixel along each ray in step 230. Then in step 240, a ray edge pixel on the ray is identified based on a maximum edge metric. Then the pixels on the ray from the local maximum to the  
30 ray edge pixel, inclusive, are labeled as belonging to the object or feature in step

250. Additional pixels belonging to the feature are labeled if they are adjacent to a labeled pixel and if the unlabeled pixel satisfies intensity and distance criteria described later. These criteria implement the unique hill climbing procedure of the present invention. This growth of labeled pixels is indicated by step 216. In step 5 270, every unlabeled pixel next to a labeled point is examined using the criterion in step 260 until no further points can be labeled.

Figure 2B shows steps that follow step 270 in another embodiment of the present invention. Here each of the labeled pixels is checked in step 275 and those labeled pixels adjacent to an unlabeled pixel are relabeled as an edge pixel of the 10 small feature. This completes the labeling associated with one of the small features in the image; and, in step 280, control is returned to step 210 until no local maximum remains unlabeled or unsegmented in the image. In yet another embodiment of the invention, small features identified in the image can be joined in step 285 if those pixels are within a joint distance. Additional detail regarding 15 the steps shown in Figures 2A and 2B are provided with reference to Figures 2C through 5.

According to the present invention, the segmentation is based on the experience that, in a given array, the edge of a small feature to be segmented is a closed contour around a local intensity extreme pixel  $P_0$ . In the preferred 20 embodiment, the local intensity extreme is selected as the pixel with an extreme intensity (maximum or minimum) in a region the size of the expected size of the small feature or object. The region should have the same number of dimensions as the data array, just fewer pixels. In other words, the region is defined as a sub-array of the multidimensional size equal to the expected size of the feature. In the 25 case of mammograms, this sub-array is a square that is about 100 pixels in x and 100 pixels in y when the resolution of the image is about 25 microns per pixel. To avoid selecting local extremes that are insignificant, the extreme is also required to achieve a certain absolute value -- above a pre-set bright threshold in the case of a local maximum, or below a pre-set dark threshold in the case of a local 30 minimum.

- A pixel  $P$  on a ray is considered to be on the edge of a small object if it provides a maximum edge metric in a line search on a ray originating from the local extreme pixel and moving in a direction  $k$ . The edge metric may be defined as the change in intensity with each succeeding pixel in the direction  $k$  or by a
- 5 Sobel operator centered on the pixel, or by any known edge metric. However, in the preferred embodiment with a local maximum, a ray edge pixel is found that more closely corresponds to that selected by expert analysis when the edge metric is a slope defined according to equation 3.

$$S(P) = \frac{f(P_0) - f(P)}{d(P_0, P)} \quad (3)$$

- 10 For each pixel  $P$  around this local maximum  $P_0$  the slope has a value  $S(P)$  where  $f(P_0)$  is the intensity, e.g., the gray scale value, at the local maximum pixel  $P_0$ , and  $f(P)$  is the intensity at pixel  $P$ , and  $d(P_0, P)$  is the distance between the local maximum pixel  $P_0$  and the pixel  $P$ . In general, to extend to the case where  $P_0$  is a local minimum, the absolute value of the numerator is used. The notation  $d(P_1, P_2)$
- 15 here indicates the absolute value of the distance between two points  $P_1$  and  $P_2$ . Let  $P_n$  represent the  $n$ th pixel along a ray in a direction  $k$ . The  $n$  varies from 0 at the local maximum to  $N-1$  at the  $N$ th consecutive pixel along the ray. The number  $N$  is not a critical choice as long as it is larger than the number of pixels expected to lie between the local maximum and the edge of the largest structures of interest.
- 20 Referring to Figure 3,  $N$  should be the number of pixels extending half the length of the arrow 330 indicating the maximum expected size of a small feature, for example. Among the pixels  $P_n$ , the pixel at which  $S(P_n)$  is maximal is considered to be an edge point in that direction and is denoted by  $e(k)$ . In the preferred embodiment, the ray search is applied in many equally spaced directions
- 25 originating from the local maximum pixel, resulting in a set of ray edge pixels  $e(k)$  where  $k$  varies from 1 to  $K$ , the number of directions for which rays are computed. In the preferred embodiment, as shown in Figure 3,  $K$  equals 16. For each direction  $k$ , the edge pixel and all pixels between the local maximum and the edge pixel  $e(k)$  are labeled as belonging to the object associated with the local



maximum pixel  $P_0$ . This results in  $K$  radial lines of labeled pixels 350, as shown in Figure 3. These labeled pixels are used as seeds or reference pixels for growing a region to identify all the pixels of the object.

To identify all pixels lying within a contour including the edge points  $e(k)$ ,  
 5 the region should grow essentially on pixels with more extreme intensity (e.g., increasing intensity) and toward the local extreme (e.g., local maximum). From any labeled pixel taken as a reference point, the region can grow to an adjacent unlabeled pixel if this new pixel satisfies some particular conditions. In the case of data arrays with more than two dimensions, adjacent points to a labeled point  
 10 are those whose indices are all within one of the corresponding indices of the labeled point. Referring to Figure 4, the reference pixel is the labeled pixel 420 and the eight adjacent pixels are numbered clockwise from the diagonally upper left pixel as pixel 1 through 8. These eight pixels are considered eight-connected with the labeled pixel 420. A subset of these adjacent pixels is the four-connected  
 15 set of pixels to which pixels labeled 2, 4, 6 and 8 belong. With respect to the reference or labeled pixel 420, an eight-connected adjacent or neighbor pixel is checked. If the neighbor pixel is already labeled, it has already been determined that the neighbor pixel is on the object. If the neighbor pixel  $P$  is not labeled, then it has to satisfy the following conditions to be labeled.

20 IF  $f(P) \geq f(P_r)$  then  $P$  must be in a position that constitutes a step from  $P_r$  toward  $P_0$ .

IF  $f(P) < f(P_r)$ , then  $P$  should be closer to  $P_0$  than  $P_r$  is to  $P_0$  by more than a minimum distance called an inclusion tolerance distance.

All pixels labeled during the process are used as reference pixels. The  
 25 method stops when no pixel can be appended as shown in step 270 of Figure 2A. The step for labeling unlabeled pixels is illustrated in Figure 2A as step 260.

The intensity and distance criterion referred to in step 260 are now described with reference to Figures 2C and 2D, which each show one of the two alternative criteria used in the present hill climbing method and apparatus. In both  
 30 these figures, the first condition checked is the intensity  $f(P)$  of the unlabeled

point P compared to the intensity  $f(P_r)$  at the reference pixel  $P_r$ , as shown in step 262.

Most microcalcifications have an intensity that decreases monotonically from the local maximum toward the edges. However, in some cases, this may not be true, and the growth toward the local maximum may need to include new pixels that have lower values or less extreme values than their labeled referenced pixels. As long as this is done strictly toward the local extreme, growth in an unwanted direction is avoided. That is, if the unlabeled pixel P is much closer to the local maximum (or minimum) than is the labeled referenced pixel  $P_r$ , then the unlabeled pixel P is considered engulfed by the object and is labeled even if its intensity  $f(P)$  is less extreme than  $f(P_r)$ . The distance by which the unlabeled point must be closer than the labeled point to be engulfed by the object is called the inclusion tolerance distance. In this and the following discussions, the difference in distances between the labeled and unlabeled points to the local maximum  $P_0$  is represented by G given in Equation 4.

$$G = d(P_0, P) - d(P_0, P_r) \quad (4)$$

When the unlabeled pixel P is closer to the local maximum  $P_0$  than the unlabeled pixel  $P_r$ , then G is negative. Therefore, the negative of G is compared to the inclusion tolerance to determine if the unlabeled pixel is close enough to the local extreme to be engulfed, as shown in step 263 of Figures 2C and 2D. In the preferred embodiment, the inclusion tolerance is one pixel. Thus, lower intensity pixels closer to the local maximum than the already labeled point  $P_r$  by more than one pixel are close enough to be labeled. That is, a new pixel P with intensity  $f(P)$  less extreme than the intensity  $f(P_r)$  of the referenced pixel  $P_r$  is appended to the region if its distance to the local extreme is such that  $-G$  is  $\geq$  the inclusion tolerance distance, as shown in step 265 of Figures 2C and 2D. If the unlabeled pixel with less extreme value is less than the inclusion tolerance closer to the local extreme or is farther from the local extreme, then the unlabeled pixel is not labeled, as shown in step 265 of Figures 2C and 2D.

The other branch from step 262 in Figures 2C and 2D is followed when the adjacent pixel P that is unlabeled has an intensity that is greater than or equal to the intensity of the labeled pixel  $P_r$ . This corresponds to the condition in the case of a local minimum that the unlabeled pixel has a lower intensity than the labeled pixel  $P_r$ . That is, the “yes” branch is followed from box 267, in general, if the unlabeled pixel P has an intensity that is no less extreme than the intensity at the labeled pixel  $P_r$ . Each of two different criteria can be used to determine whether the unlabeled pixel P is in a position that constitutes a step from the labeled pixel  $P_r$  toward the extreme pixel  $P_0$ .

The first criterion, Criterion 1, is indicated in Figure 2C and step 264a and is based on the angle of the line perpendicular to the line segment connecting the local extreme  $P_0$  with the reference pixel  $P_r$ . The line perpendicular to the segment connecting the local extreme to the labeled pixel is called the reference line 430 and is shown in Figure 4. For arrays of more than two dimensions, the reference would be a surface with a number of dimensions at least one dimension less than the multidimensional array. The numbered pixels of Figure 4 are approved for appending to the small feature if they fall within the list of approved pixels listed in Table 1 for the quadrant in which the angle  $\theta$  varies from 0-90°. The angle  $\theta$

20

**Table 1. Criterion 1 for First Quadrant.**

$x_r$	$y_r$	$\theta$	Approved Pixels
$x_r = x_0$	$y_r < y_0$	$0^\circ$	1, 2, 3, 4, 8
$x_r > x_0$	“	$0 < \tan \theta \leq 1/3$	1, 2, 3, 4, 8
“	“	$1/3 < \tan \theta < 1$	1, 2, 3, 8
“	“	$\tan \theta = 1$	1, 2, 3, 7, 8
“	“	$1 < \tan \theta \leq 3$	1, 2, 7, 8
“	“	$3 < \tan \theta < \infty$	1, 2, 6, 7, 8
“	$y_r = y_0$	$90^\circ$	1, 2, 6, 7, 8

between the reference line 430 and the  $x$ -axis is also shown in Figure 4. The first two columns of Table 1 show the relationship between the coordinates of the reference pixel  $x_r$  and  $y_r$  of  $P_r$  and their relationship to the coordinates  $x_0$  and  $y_0$  of the local maximum  $P_0$ . For different values of the angle  $\theta$  or its tangent,  $\tan \theta$ ,  
5 different of the numbered pixels in Figure 4 are approved. Table 1 captures the condition that the unlabeled pixel  $P$  and the local maximum  $P_0$  must lie on the same side of the reference line 430. Among the eight pixels that surround a reference pixel, only some will meet the spatial criterion of Criterion 1, depending on the angle  $\theta$  of the reference line. The angle  $\theta$  is measured positive  
10 counterclockwise from the  $x$ -axis. The allowable pixels for values of  $\theta$  in the other three quadrants are obtained in a symmetrical manner. An extended table would have to be drafted for data arrays of greater than two dimensions.

As an alternative for the constraint C1 described above and summarized in  
15 Table 1, Constraint 2 can be used to determine whether a neighboring pixel should be labeled. Constraint 2 is more readily extensible to more than two dimensions. Referring to Equation 4 defining the distance difference  $G$ , most allowable pixels described by Criterion 1 yield a negative  $G$  value. However, some pixels generate a positive  $G$  value. These positive  $G$  pixels are the pixels  
20 that provide a step, from the reference pixel  $P_r$ , approximately parallel to the reference line. This type of growth through pixels is especially desirable around the edge of the small structure. The largest values of  $G$  are associated with diagonal pixels and occur at the edge of the smallest features to be segmented. Furthermore, among all possible pixel configurations, the value of  $G$  is maximal  
25 when the reference line angle  $\theta$  is  $45^\circ$  or  $135^\circ$  and the new pixel  $P$  is diagonally connected to the referenced pixel  $P_r$ . This maximal value is also obtained for other homologous arrangements of the three pixels. A positive threshold  $G_t$  for  $G$  can be used instead of Criterion 1. Consider an approximately circular object  $2N$  pixels wide. On the edge of such an object, the highest value for  $G$ , called  $G_{\max}$ , will  
30 equal  $(\sqrt{N^2+2})-N$ . The smaller  $N$ , the larger  $G_{\max}$  will be. An appropriate

threshold for  $G$  can be set by using the width of the smallest object of interest. Therefore, an alternative way of constraining the expansion of pixels away from the local extreme is to allow only new pixels which provide a value of  $G$  of at most  $G_{\max}$ . That is, set  $G_t = G_{\max}$ . This threshold,  $G_t$ , can be considered an expansive tolerance distance. Criterion 2 can be stated as:  $G$  must be less than or equal to the expansive tolerance distance,  $G_t$ . For example, mammograms with pixels of 25 microns and microcalcification candidates having structures as small as 0.25 mm across, yield  $N=5$ ; so,  $G_t = G_{\max} = 0.196$ .

The preferred embodiment determines 16 ray edge pixels around the object, and segments with the hill climbing procedure described. As indicated in step 270 of Figure 2A, each appended pixel is labeled and is used as a reference pixel itself during growth. The growth stops when no pixel can be appended. Once no more new pixels can be labeled, each labeled pixel is examined to identify edge pixels of the small feature in step 275 in Figure 2B. The edge pixels of the small feature are determined to be all labeled pixels that are four-connected to an unlabeled pixel after no further pixels can be added.

After every object has been segmented and its outer edge pixels defined, larger features may be discernable. The larger features can be constructed where the small features abut or overlap slightly. The step of joining small features together into a larger feature is depicted in step 285 of Figure 2B. Depending on the larger feature being assembled, the criterion for joining small features can be that the small features share edge pixels, or that the edges overlap so that the edge of one small feature is an interior labeled pixel of another small feature. It is also possible that features be joined that do not touch or overlap, provided they are sufficiently close together. A tolerance called a join distance can be used to determine how close the edges should be to each other in order to combine the small features into one or more larger features. In this case, all small features are joined where the edge pixels of two different small features are within a join distance. Overlapping pixels are covered by this criterion as are features whose

edge pixels coincide. By setting the joined distance to 0 the edge coincidence is required; and by setting the join distance negative, overlapping can be required.

### EXAMPLES

To determine whether the results of the present invention provide edges of  
 5 small features that are useful in interpreting mammograms and in doing so with  
 fewer computations than other methods, several experiments were performed with  
 actual mammograms. The correctness of the edge determined by the present  
 invention is measured by its similarity to the edges determined by an analyst, and  
 its ability to discriminate among the candidate microcalcifications in subsequent  
 10 processing. Other advantages of the preferred embodiment are measured using the  
 complexity or number of computations involved in the procedure, and the time  
 required to execute the procedure on a computer.

#### Example 1

Five mammograms containing subtle microcalcification clusters were used  
 15 to evaluate the algorithms for data that would warrant the use of an automated  
 system. Mammograms without magnification were used; and the breast images  
 covered an area that ranged between 12cm x 6cm and 21cm x 11cm. The location  
 of individual microcalcifications was indicated by an experienced  
 mammographer. These 5 mammograms contained 15 clusters with a total of 124  
 20 microcalcifications, yielding about 8 microcalcification per cluster. The number  
 of microcalcifications per cluster ranged between 3 and 18. The size of  
 microcalcifications ranged between 0.25mm and 1mm wide, with more than 90%  
 being smaller than 0.5mm. Mammograms were digitized with a Howtek D4000  
 drum scanner using a spatial resolution of 25 microns per pixel and 12-bit A/D  
 25 conversion, with an optical dynamic range of 0-3.5 optical depths (O.D.).

The multi-tolerance region growing procedure grows a region around a  
 seed pixel by appending 4-connected pixels P that satisfy:

$$(1+\tau)(F_{\max}+F_{\min})/2 \geq P \geq (1-\tau)(F_{\max}+F_{\min})/2 \quad (5)$$

where  $\tau$  is the tolerance parameter, and  $F_{\max}$  and  $F_{\min}$  are the current maximum and minimum values in the region grown that far. The value of  $\tau$  is not manually selected by the user; the best value is automatically determined for each segmented structure by repeating the growth with multiple values of  $\tau$  between  
 5 0.01 and 0.4 with steps of  $s=1/v$ , where  $v$  is the 8-bit value of the seed pixel. Three features are extracted from each region grown with a different tolerance level: shape compactness, center of gravity, and size. The algorithm determines the value of  $\tau$  that results in the minimal change in the vector of these three features with respect to the previous  $\tau$  value in the sequence by computing a  
 10 normalized difference between consecutive vectors. The vector with minimal difference indicates the best choice of  $\tau$ .

The segmentation outcome of the multi-tolerance region growing procedure on 5 subtle microcalcification candidates depended partly on the intensity structure of the microcalcification. When the intensity transition from the  
 15 edge to the background was relatively abrupt, the segmented region coincided closely to the visually perceived edge. When the intensity at the edge decreased gradually toward the background level, this algorithm generally produced a relatively large region. Nevertheless, the growth was consistently contained, i.e. it did not grow to an unacceptable size and it generated boundaries that can be used  
 20 as an estimate of the immediate background around the microcalcification.

The active contours model represents the contour points as  $v(s)=(x(s),y(s))$ . The contour is obtained by minimizing the energy functional:

$$E[v(s)] = \int_{\Omega} [E_{\text{int}}[v(s)] + PE[v(s)] + E_{\text{ext}}[v(s)]] ds \quad (6)$$

where  $E_{\text{int}}$  is the internal energy due to the elasticity and the rigidity,  $PE$  is the  
 25 potential energy obtained from the image data,  $E_{\text{ext}}$  is the energy of external forces that can be applied to the contour. The integration is performed over the entire contour  $\Omega$ . The internal energy is expressed by:

$$E_{\text{int}} = w_1 |v'(s)|^2 + w_2 |v''(s)|^2 \quad (7)$$

where  $w_1$  and  $w_2$  are coefficients that control the elasticity and rigidity, respectively, and primes denote differentiation. The choice of potential energy depends on the application; it is typically the negative squared gradient magnitude, and is so used for mammograms.

5        The active contour that minimizes  $E(v)$  satisfies the Euler-Lagrange equation:

$$-(w_1 v')' + (w_2 v'')'' = F(v) \quad (8)$$

where  $F(v)$  represents the force due to the combined effects of the potential energy and external energy. In this study we implemented the balloon forces and the  
10    image force normalization suggested, resulting in

$$F(v) = k_1 n(s) - k_2 \frac{\nabla P E}{\|\nabla P E\|} \quad (9)$$

where  $n(s)$  is the unit vector normal to the contour at point  $v(s)$ , oriented toward the outside of the contour,  $k_1$  is the magnitude of the balloon inflation force, and  $k_2$  is the coefficient of the normalized image force. The value of  $k_2$  is selected to  
15    be slightly larger than  $k_1$  to allow edge points to stop the inflation force.

The numerical solution was implemented using finite differences and the iterative evolution as suggested:

$$(I + \tau A) v_t = (v_{t-1} + \tau F(v_{t-1})) \quad (10)$$

where  $I$  is the identity matrix,  $\tau$  is the time step,  $A$  is the pentadiagonal matrix  
20    obtained with the finite difference formulation of  $E_{\text{int}}$ ,  $v_t$  is the active contour vector at time  $t$ , and  $F(v_t)$  is the external force vector at time  $t$ . We used the negative squared magnitude of the image gradient as the potential energy. Pixels detected with an edge detector were not used in this study. The gradient of the image was computed with the Sobel operator.

25        The initial position of the contour was set automatically for each structure to be segmented. Since each structure of interest is a local intensity extreme, pixels were selected that were local maxima across the entire image. Each local maximum was used to segment a region around it. The width of the smallest microcalcifications considered in this study was about 0.25 mm and the majority



of the microcalcifications in our database had widths in the range 0.3 to 0.5 mm. A circle of 0.2 mm diameter around the local maximum pixel was used as the initial position of the active contour. The initial contour points were 24 8-connected pixels forming this circle.

5        The selection of parameters for the active contour segmentation required some trial and error to obtain good segmentation. The segmentation of the same 5 subtle microcalcification candidates was performed using different active contours parameters. First, following the recommendations of Cohen (Cohen, L.D. "On Active Contour Models and Balloons," *CV GIP: Image Understanding*, vol. 53, 10 pp. 211-218, 1991), we selected the values of  $w_1$  and  $w_2$  as a function of the spatial discretization step size  $h$ , such that  $w_1$  was of the order of  $h^2$  and  $w_2$  was of the order of  $h^4$  ( $w_1=6$ ,  $w_2=40$ ). Then  $\tau$  was also set to 0.1. When  $k_1$  and  $k_2$  were relatively small (2 and 4), the image force and the balloon force did not act sufficiently on the active contour, producing contours that were only slightly 15 different than the initial position. When these two parameters were increased (14 and 16), the resulting segmentation was very close to that expected visually. Increasing these parameters further (24 and 26) increased the combined effect of image gradient and balloon forces, producing contours that extended beyond the expected edges. Within this range, segmentation with the active contour model 20 was not very sensitive to the values of the other parameters. The effect of doubling  $w_1$  to 12, is that contours became slightly smaller due to the increased stiffness of the active contour model. Sensitivity to  $w_2$  was also low. When  $w_2$  was doubled to 80, the contours became slightly smoother due to the increased rigidity of the model.

25        The segmentation steps of the hill climbing approach of the present invention are illustrated in Figure 6. Figure 6A shows a microcalcification candidate that has a width of about 0.3 mm. The 16 ray edge points 624 determined by the radial line search of the hill climbing algorithm are shown in Figure 6B. The region grown using spatial Constraint 1 is in Figure 6C. The 30 region grown with spatial Constraint 2 was identical for this microcalcification

candidate. The edge pixels 642 of the entire microcalcification candidate are shown in Figure 6D. The segmentation of microcalcifications by the hill climbing method produces outcomes using the spatial Constraints 1 and 2 that were almost identical. In this study, about a quarter of microcalcifications were segmented  
 5 identically by the two spatial constraints and the rest differed by a few pixels, resulting in a negligible change over the entire microcalcification. Both spatial constraints directed the growth of the regions successfully, resulting in regions that were compatible with visual interpretation.

The differences between the three methods are illustrated in Figure 7.  
 10 Three subtle microcalcifications candidates are shown in Figure 7A. When the contrast of a microcalcification candidate was relatively low, or parts of it exhibited a very gradual decrease in intensity toward the background, the multi-tolerance algorithm (Figure 7B) segmented a larger region than those of the other two algorithms. Good segmentation with active contours (Figure 7C) was  
 15 obtained using  $w_1=6$ ,  $w_2=40$ ,  $\tau=0.1$ ,  $k_1=14$  and  $k_2=16$ , for all microcalcifications candidates of this study. Using these parameters, segmentation with active contours provided edges 735 that were smoother than edges 725 and 745 produced by segmentation with the other two methods. The selection of  $w_1$  and  $w_2$  provided the flexibility needed to adapt relatively well to the shape of diverse  
 20 microcalcifications candidates. The elasticity level allowed the contour to grow to the highest gradient locations when the segmented structures were relatively large, and the rigidity level allowed the contour to develop sharp bends dictated by the data in some microcalcifications. The edges 745 of regions grown by the hill climbing algorithm shown in Figure 7D were not as smooth as those 735 of the  
 25 active contours, but the convolutions were consistent with visually perceived edges around microcalcifications candidates.

### Example 2

Segmentation of microcalcification candidates serves as an initial step for discriminating between the population of microcalcifications and that of

background structures. The discrimination potential of each segmentation algorithm was quantified using features extracted from structures segmented around all the local maxima in the 5 mammograms. These structures consisted of the 124 microcalcifications mentioned above and 2,212 background structures segmented in the same mammograms. Four characteristics were used to assess the discrimination potential in this study.

1. *Contrast* was measured as the gray level difference between the local maximum pixel  $P_0$  in the structure, and the mean of pixels around its edge.
2. *Relative contrast* was computed as the ratio of the *contrast* to the value at the local maximum.
3. *Area* was computed as the number of labeled pixels in the grown region.
4. *Edge sharpness* was the mean of the gradient computed with a Sobel operator across all edge pixels. The Sobel operator is a mask which weights the eight neighbors of a pixel to compute a sum proportional to the gradient x, or the y gradient, or total gradient.

The discrimination ability of each feature was determined separately using the area under a receiver operating characteristic (ROC) curve obtained with that feature. The ROC curve plots the percentage of correctly detected microcalcifications against the percentage of detected background structures as a detection threshold is changed. The ROC curve area is higher when the feature has distributions that are more separable for a given property. When both populations overlap completely, the ROC curve area is 0.5. In general, effective discrimination power is indicated by a value above 0.8. Table 2 summarizes the results for all three procedures. The area feature had very low discrimination power for all three algorithms, indicating that the two types of structures cannot be discriminated well on the basis of their area segmented. However, the other

**Table 2**

Multi-tolerance	Active Contours	Hill Climbing
Region Growing		

Contrast	0.80	0.82	0.83
Relative Contrast	0.83	0.90	0.90
Area	0.63	0.60	0.54
Sharpness	0.80	0.85	0.85

three features suggested good discrimination potential for all three algorithms. A comparison among algorithms shows that both the hill climbing method of the present invention and the active contours algorithm provide segmentation with the same discrimination power, and they both perform slightly better than the multi-  
5 tolerance segmentation. Thus, the hill climbing method produces edges as good as the best produced by the conventional approaches tested.

The significant advantage of the hill climbing algorithm is its speed. While the multi-tolerance algorithm provides a good solution to avoid the use of statistical models, local statistics estimators and the manual selection of threshold,  
10 its cost is multiple segmentations of the same structure and computation of features during the segmentation of each structure. Furthermore, in some cases, this algorithm segments regions that are somewhat larger than expected. Consequently, the time required for segmentation of a mammogram with this algorithm is high. The segmented regions were comparable to those of the other  
15 two algorithms in many cases. The differences were caused by the fact that the growth mechanism of this algorithm is constrained only by an intensity range criterion applied to a new pixel. In contrast, active contours are constrained by internal forces that regulate the growth away from the local maximum, and hill climbing has an inward growth mechanism based on edge points.

20 The active contours also circumvent the statistical and manual threshold selection issues for each mammogram, but the selection of the operational parameters for a set of mammograms requires some trial and error. However, when an appropriate set of parameters is determined, it appears to be valid for a wide range of microcalcifications so it need not be modified with each

mammogram. The choice of negative squared gradient magnitude as the image energy function seems to be an appropriate one to segment microcalcifications.

### Example 3

The computational complexity  $c_m$  of the multi-tolerance region growing algorithm is of the order  $O(4smo)$  where  $s$  is the number of steps in the tolerance search,  $m$  is the number of pixels in the region, and  $o$  is the number of operations per pixel. The factor 4 is included because the algorithm visits the 4-connected neighbors for each pixel in the region. Considering 125 to be an average intensity value for the local maximum, the average step size is 0.008 resulting on the average in about  $s=50$  steps to cover the range 0.01 to 0.4. The average size of segmented structures is about 200 pixels. At each pixel the computations performed include intensity comparisons, update of  $F_{\max}$  and  $F_{\min}$ , and calculation of the center of gravity. Considering about 12 operations per pixel on the average, the numerical estimate for the average number of operations per segmentations is  $c_m=480,000$ .

The computational complexity  $c_a$  of the active contour model is  $O[2(n+n^2)t]$  where  $n$  is the number of contour points, and  $t$  is the number of iterations. The factor of 2 is included due to the fact that the  $x$  and  $y$  coordinates of each contour point are computed separately, with identical operations. At each iteration, order  $n$  computations are needed to determine the normal vectors, and order  $2n^2$  operations are needed to perform a matrix multiplication. In this study 24 contour points were used, and the number of iterations depended on the size of the structure. On the average however, the active contour model converged in about 20 iterations. This resulted in an average value of  $c_a=47,040$ , a factor of ten improvement over the multi-tolerance method.

The complexity  $c_h$  of the hill climbing method is  $O(KN + 8m)$  where  $K$  is the number of radial directions from the local maximum,  $N$  is the number of pixels searched in each direction, and  $m$  is the number of pixels in the grown region. A factor of 8 is included since all 8 neighbors of each pixel are visited. In

this study  $K$  was 16 and  $N$  was 40, and considering an average structure size of  $m=200$ , the average estimate of the number of operations is  $c_h=2,240$ , a factor of 20 improvement over the active contour methods, and 200 over the multi-tolerance method. The proportions of  $c_m$ ,  $c_a$  and  $c_h$  are approximately 214:21:1  
 5 respectively, with hill climbing far less complex than the other two methods.

#### Example 4

The speed of the different methods was compared using a section of a mammogram containing 456 local maxima, 35 of which were in microcalcifications. The sizes of microcalcifications ranged between 0.25 mm and  
 10 0.5 mm. The times to complete the segmentation of this section of mammogram using the three algorithms implemented in C on a 10 million floating point operations per second (MFLOPS), IBM 6000 computer were 17 minutes 47 seconds for the multi-tolerance algorithm, 1 minute 47 seconds for the active contours, 7 seconds for hill climbing with spatial Constraint 1, and 5.4 seconds for  
 15 hill climbing with spatial constraint 2.

Hill climbing with spatial Constraints 1 and 2 yielded practically identical segmentations; but the method was about 20% faster using spatial constraint 2, resulting in 11.8 ms on average for segmenting a structure, as opposed to 15.3 ms obtained with spatial Constraint 1.

20 A common technique to determine the edges of an object uses an edge enhancement algorithm such as the Sobel operator, thresholding to separate the pixels on edges, and pixel linking to string edge pixels that belong to the same object. Selection of the threshold is critical, and linking poses problems in segmenting microcalcifications because there are many closely spaced small  
 25 structures in a background that are likely to produce considerable numbers of edge pixels. The hill climbing method of the preferred embodiment determines edge points that are on the edge of the same object by virtue of the radial line search emanating from the same local maximum. It does not require a threshold to separate edge pixels because the slope in Equation 3 is referred to the local

maximum and is greatest at pixels that are on, or very near, the visually perceived edges. Finally, the hill climbing method avoids some pitfalls of the region growing mechanism by growing a region inward, toward the local maximum.

5        There has been disclosed a segmentation method and apparatus for data arranged in a multidimensional array which overcomes the problems of the prior art. Although the present invention has been described above by way of detailed embodiments thereof, it is clearly understood that variations and modifications may be made by one of ordinary skill in the art and still lie within the spirit and scope of the invention as defined by the appended claims and their equivalents.